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Intracortical neural representation of finger movements in a nonhuman primate preserved over 400 days

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Introduction: Most motor brain-computer interfaces (BCIs) require calibration on the day of use. To reduce the burden of calibration, the decoding algorithm, which maps neural activity to a control signal for a device, can be realigned from day to day or subject to subject [1, 2]. These approaches rely on the underlying principle that the neural inputs can be transformed into a stable representation across days, enabling a static decoder to infer motor movements. While these techniques were developed for single effectors, we investigated whether neural data can be transformed into a stable representation of multiple individuated finger movements using latent factor analysis via dynamical systems analysis (LFADS) [3, 4]. We also explored whether this stable representation can be inferred – without recalibration – from neural inputs conditioned only by channel statistics.

Material, Methods and Results: During 12 sessions spanning 427 calendar days, intracortical recordings in the precentral gyrus and movements from the index and middle-ring-small finger groups were recorded while one monkey (nonhuman primate) performed a finger-movement task. First, to illustrate how neural instabilities degrade BCI performance, we trained a ridge regression decoder on a single day (from the 12-day set) to predict finger flexion velocity from spiking activity and used this linear decoder to predict finger movements on all subsequent days (see Fig. 1a; yellow). Prediction performance decreased with the number of days since training (5.93e-4 correlation/day; p = 1.2e-8).

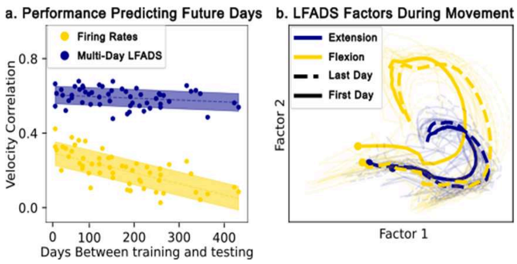

Figure 1: *(a) Finger velocity prediction performance using spiking activity (yellow) or multiday LFADS factors (blue). X-axis represents the calendar days between the day the decoder was trained and tested (b) Representative latent factors from the multiday LFADS model. Trial-averaged factors during both fingers flexing (yellow) and both fingers extending (blue) is shown in bold with thin lines representing individual trials. Results for trials during the first session (solid) and last session (dashed – 420 days later).*

To understand whether a consistent latent representation existed across days for fingers, a multiday LFADS model with session-specific read-in and read-out layers was trained over all 12 sessions. The multiday LFADS model revealed latent factors that were qualitatively similar across days (see Fig. 1b). Quantitatively, consistent latent factors allowed decoding finger movements from the factors with a static decoder. Specifically, we found that finger velocities on one day could be accurately predicted using a ridge regression decoder learned on a previous day (see Fig. 1a; blue), with little drop in performance over time (-9.8e-5 corr/day; p = 0.07).

Toward improving decoding without recalibration, we tested a static read-in network for the neural activity, which used an encoding of channel statistics (mean and covariance) as additional inputs. We trained an LFADS model with this static read-in network during the 12 sessions. On 7 held-out sessions using this pretrained model, a decoder mapping factors to finger velocity was trained on a single day and tested at the next session. This approach improved velocity predictions compared to smoothed spikes trained and tested on the same 2 days (delta corr = 0.1; p = 7e-3; paired t-test).

Conclusion: We demonstrate a consistent latent representation of fingers over 427 days using LFADs and present a pretrained decoding approach, which we are continuing to optimize and develop, that may reduce sensitivity to daily neural instabilities.

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